

Representation Surgery

Theory and Practice of Affine Steering

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Representations

LM's train to predict the next token.

LM's train to produce contextual representations (vectors for a sentence) to predict the next token.

Can we treat them as well-behaved multi-variate spaces for de-biasing and controlling generation?

Guardedness

An attribute **z** is considered guarded if we **can't** classify along that attribute.

Eg: being unable to tell the gender of a noun based on the representations from it.

Affine Concept Erasure: an Affine transformation that guards a particular attribute.

$$b(\underline{z}) = \underset{\uparrow}{w_z} + \underset{\uparrow}{b}$$

What do we want?

Make the vectors from a particular distribution look like those of another distribution.

(eg. make toxic generation vectors look like non-toxic vectors)

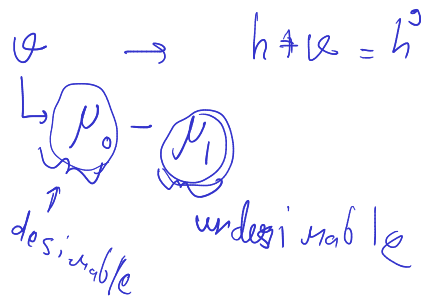
Leading to: guarding

We want to do this with the smallest change possible so as to preserve semantics unrelated to **Z**

he asked John to ... ~~fuck~~ off
↳ leave immediately

Context and related work

Steering vectors :



Debiasing

LEACE \rightarrow

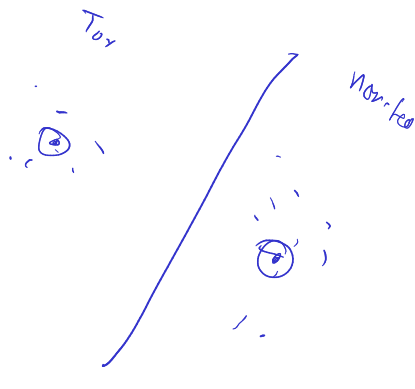
Guarding

gender

asymmetry

Contribution 1

Existing literature uses steering vectors for this kind of thing. We provide a theoretical justification to steering vectors. We phrase an optimization problem for what we want


$$\begin{cases} \underset{s \in \text{Aff}_s(D)}{\text{minimize}} \quad \mathbb{E} \left[\|\overset{\text{original}}{\downarrow} \mathbf{H} - s(\mathbf{H})\|_2^2 \right] \\ \text{subject to} \quad \mathbb{E}[s(\mathbf{H}_c)] = \mathbb{E}[s(\mathbf{H}_{c'})] \end{cases} \quad \text{inferred}$$

Affin:

Piecewise

$Wh + b$

if ()

h

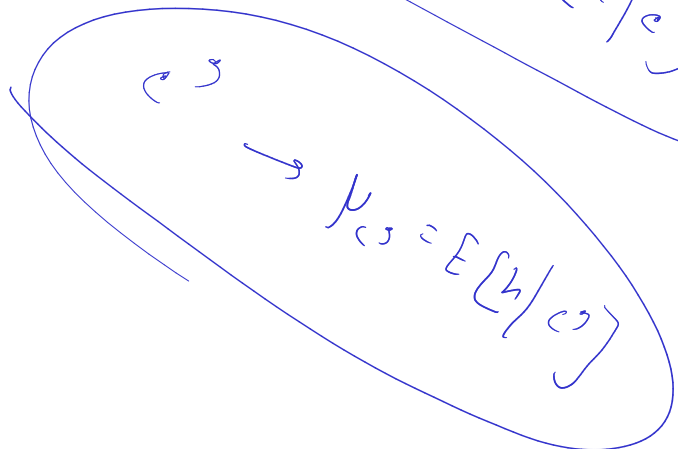
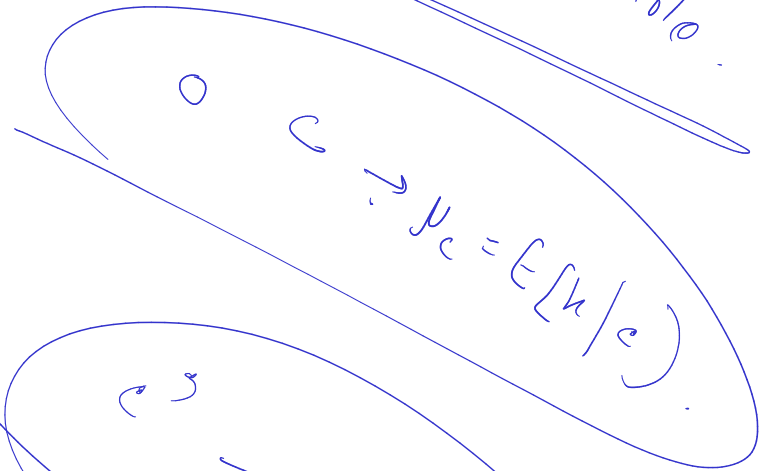
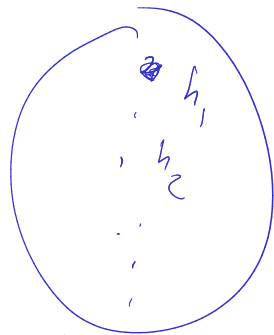
else ()

$Wh + b$

sendce

label

available



Contribution 1

Existing literature uses steering vectors for this kind of thing. We provide a theoretical justification to steering vectors. We phrase an optimization problem for what we want

$$\begin{aligned} & \underset{s \in \text{Aff}_s(D)}{\text{minimize}} \quad \mathbb{E} \left[\| \mathbf{H} - s(\mathbf{H}) \|^2_2 \right] \\ & \text{subject to} \quad \mathbb{E}[s(\mathbf{H}_c)] = \mathbb{E}[s(\mathbf{H}_{c'})] \end{aligned}$$

matching the first moment

Solution:

$$s^*(\mathbf{H})(s) = \begin{cases} \mathbf{H}(s) + \mu_{c'} - \mathbf{W}^* \mu_c & \text{if } \phi(s) = c \\ \mathbf{H}(s) & \text{if } \phi(s) = c'. \end{cases}$$

$$\mathbf{W}^* = \mathbf{I}$$

$\mu_{c'} - \mu_c \rightarrow$ undesirable,
 $\mathbf{I} \rightarrow$ desirable.

Contribution 2

We extend the optimization problem and provide a more expressive steering function.

$$\underset{s \in \text{Aff}_s(D)}{\text{minimize}} \quad \mathbb{E} \left[\|\mathbf{H} - s(\mathbf{H})\|_2^2 \right]$$

$$\text{subject to } \mathbb{E}[s(\mathbf{H}_c)] = \mathbb{E}[s(\mathbf{H}_{c'})]$$

$$\mathbb{E}[s(\mathbf{H}_c)s(\mathbf{H}_c)^\top] = \mathbb{E}[s(\mathbf{H}_{c'})s(\mathbf{H}_{c'})^\top]$$

x in same way \rightarrow matching
 \rightarrow 1 and 2
ie match mean and covariance.

1st moment

2nd moment

Contribution 2

We extend the optimization problem and provide a more expressive steering function.

$$\begin{aligned} & \underset{s \in \text{Aff}_s(D)}{\text{minimize}} \quad \mathbb{E}[\|\mathbf{H} - s(\mathbf{H})\|_2^2] \\ & \text{subject to} \quad \left. \begin{aligned} \mathbb{E}[s(\mathbf{H}_c)] &= \mathbb{E}[s(\mathbf{H}_{c'})] \\ \mathbb{E}[s(\mathbf{H}_c)s(\mathbf{H}_c)^\top] &= \mathbb{E}[s(\mathbf{H}_{c'})s(\mathbf{H}_{c'})^\top] \end{aligned} \right\} \end{aligned}$$

has the solution

$$s^*(\mathbf{H})(s) = \begin{cases} \mathbf{W}^* \mathbf{H}(s) + \mathbf{b}^* & \text{if } \phi(s) = c \\ \mathbf{H}(s) & \text{if } \phi(s) = c'. \end{cases}$$

where we define

$$\begin{aligned} \mathbf{W}^* &= \Sigma_c^{-\frac{1}{2}} (\Sigma_c^{\frac{1}{2}} \Sigma_{c'} \Sigma_c^{\frac{1}{2}})^{\frac{1}{2}} \Sigma_c^{-\frac{1}{2}} \\ \mathbf{b}^* &= -\mathbf{W}^* \mu_c + \mu_{c'}. \end{aligned}$$

Σ : covariance matrix,

Optimal transport

Implications

a no-gradient and cheap way to control generation and to de-bias.

De-biasing

Protecting attributes without damage

Model	Intervention	TPR ↓	Accuracy ↑
BERT-base	Base	0.155	0.799
	LEACE	0.137	0.797
	Postprocessing (Xian et al., 2023)	0.146	0.742
	Mean Matching	0.141	0.797
GPT-2	Mean+Covariance Matching	0.093	0.785
	Base	0.168	0.676
	LEACE	0.093	0.670
	Postprocessing (Xian et al., 2023)	0.112	0.627
Llama2-7b	Mean Matching	0.094	0.670
	Mean+Covariance Matching	0.070	0.660
	Base	0.143	0.786
	LEACE	0.133	0.795
Llama2-7b	Postprocessing (Xian et al., 2023)	-	-
	Mean Matching	0.139	0.797
	Mean+Covariance Matching	0.085	0.783

$Y = y$
doctor
multi class : gender
classifies profession

$$\text{TPR-Gap}(y) = \mathbb{E}_{\mathbf{h}_c \sim \mathbb{P}(\mathbf{H}_c | Y=y)} \mathbb{P}(\bar{Y} = y | \mathbf{H}_c = \mathbf{h}_c) - \mathbb{E}_{\mathbf{h}_{c'} \sim \mathbb{P}(\mathbf{H}_{c'} | Y=y)} \mathbb{P}(\bar{Y} = y | \mathbf{H}_{c'} = \mathbf{h}_{c'})$$
$$\text{TPR}_{\text{RMS}} = \sqrt{\frac{1}{K} \sum_{k=1}^K \text{TPR-Gap}(y_k)^2}$$

Multi-class classification that should be unaffected by gender

Perspective

Controlling generation

Experiments:

Evaluating maximum toxicity of sentences

Model	Exp. Max. Tox. ↓	Tox. prob. ↓	Fluency ↓	1-gram ↑	2-gram ↑	3-gram ↑
GPT-2 (large)	0.39	0.25	24.66	0.58	0.85	0.85
DAPT	0.27	0.09	30.27	0.57	0.84	0.84
GeDI	0.24	0.06	48.12	0.62	0.84	0.83
PPLM (10%)	0.38	0.24	32.58	0.58	0.86	0.86
UDDIA	0.24	0.04	26.83	0.51	0.80	0.83
DExperts (large, all jigsaw)	0.21	0.02	27.15	0.56	0.84	0.84
GOODTRIEVER	0.22	0.04	27.11	0.58	0.82	0.83
Mean Matching	0.33	0.16	28.00	0.58	0.85	0.85
Mean+Covariance Matching	0.29	0.09	30.7	0.54	0.84	0.84

No fine-tuning control

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